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Cognitive Factors in Students' Academic Performance Evaluation using Artificial Neural Networks

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Abstract
Performance evaluation based on some cognitive factors especially Students' Intelligent Quotient rating (IQR), Confidence Level (CoL) and Time Management ability gives an equal platform for better evaluation of students' performance using Artificial Neural Network. Artificial Neural Networks (ANN) models, which has the advantage of being trained, offers a more robust methodology and tool for predicting, forecasting and modeling phenomena to ascertain conformance to desired standards as well as assist in decision making. This work employs Machine Learning and cognitive science which uses Artificial Neural networks (ANNs) to evaluated students' academic performance in the Department of Computer Science, Akwa Ibom State University. It presents a survey of the design, building and functionalities of Artificial Neural Network for the evaluation of students' academic performance using cognitive factors that could affect student's performances.
Keywords: Cognitive, Intelligent Quotient Rating, Machine Learning, Artificial Neural Network.

1. Introduction
The technological development, economical advancement and the academic productivity of any nation, amongst other important factors, take their root in the proper and comprehensive education of her citizens – both formal and informal education: the kind of education that targets the mental advancement of the learner or the students as the case may be. No new advancements could be achieved unless new ways of doing things are discovered through the learning process. This learning process however, is often hampered by the various challenges faced in the educational system, prominent of which is the issue of poor academic performances. Every school of higher learning aims at evaluating and predicting students' academic performances to determine the categories of students that are intelligent, average or poor (Jateen Shet Shidodkar & Viren Pereira, 2016). This evaluation serves as the basis for awarding certificates to students especially in Nigerian Universities. It can be inferred therefore that the credibility, reputation and global brand and appeal of institutions of higher learning are judged partly by the quality and performances of the students and their achievements even after graduation.
The subject of poor academic performances in Nigerian Universities is an issue of great concern especially considering the fact that poor performances could surface in many other areas of life's pursuit if not effectively tracked and rectified at the academic level. The Federal Government of Nigeria in a bid to track this trend set in motion the Students Industrial Work Experience Scheme (SIWES) by establishing the Industrial Training Fund (ITF) aimed at enhancing the practical aspect of the students' learning (Ufot, U. F., Udom, I. & Nathaniel, E. U, 2016).In the past two decades, the study of student performance has become a major area of interest to researchers who keep searching out optimal solutions needed to boost the performance of students, define better teaching methods as well as enhance the effectiveness of the educational system. There have been several studies targeted at exploring the impact made to the subject of academic performance using numerous different variables based on diverse different perspective (Mariel F. Musso, Eva Kyndt, Eduardo C. Cascallar, Filip Dochy, 2013). The inability of some students to perform well academically often poses serious questions to the students involved, the lecturers who spend time and efforts in ensuring that students are adequately equipped, the parents of these students as well as the industries out there who bemoan the half-baked work force graduated from our institutions of higher learning.

The results obtained from evaluating students' academic performance in Akwa Ibom State University can be employed in analyzing better ways to teach each group of students with special consideration placed on each student's individual abilities as opposed to the average ability of the group in view. It can also be used in discovering better approaches to impacting knowledge as well as enabling educational managers to offer additional support to low performing students. The students also may use these results to improve their academic performance by developing a good understanding of how well or how poor they could perform by the knowledge of the facts made available by this research and hence develop a suitable learning strategy as well as make informed career choices. Evaluating and understanding the most outstanding factors that best indicate the causes of poor and high performances would be a much appreciated tool for better management of academic and educational resources at all levels of the educational process (M. F. Musso et al. 2013).

Optimal evaluation of academic performances is a necessity that can help enhance the quality of education in Akwa Ibom State University as well as ensure that the University provides better educational services by employing more optimal techniques. Furthermore, accurate placement of students in different course areas based on their cognitive strengths would go a long way to avoiding possible failures (M. F. Musso et al. 2013). Tracking academic performances offer, in addition, a wider knowledge on the relationships existing between the various cognitive factors that affect the overall performances of students and how these relationships can be better adapted to increase the performance of the research group.

Amongst other predictive means like Quantitative methodologies including Regression Analysis, Auto Regressive Integrated Moving Average (ARIMA) or the Markov Analysis; a predictor which uses historical data, considered in recent researches, it has been extensively realized that the Artificial Neural Network (ANN) has been by far the most successful predicting tool due to its effectiveness at capturing and representing parameters such as pattern or trend in data or seasonality (Shidodkar & Viren, 2016).

This research work therefore employs Artificial Neural Network (ANN) models to evaluate students' academic performances using variables and parameters unique to students in educationally less privileged regions of Nigeria with particular focus on the students of Akwa Ibom State University. These variables and parameters includes tests based solely the individual student's cognitive abilities using factors such as Intelligent Quotient Rating (IQR), Confidence Level (CoL), Time Management skills as well as personal motivations and inspiration which contributes to their class attendance level.

Therefore, to effectively evaluate students' academic performance, this work employs Machine Learning and cognitive science which uses Artificial Neural networks (ANNs) and factors such as the Intelligent Quotient Rating of the Students, Confidence Levels and Time Management ability. These factors provide a platform for a fair evaluation as each study is tested within their areas of strength. By using the scientific method of a multilayer perceptron neural network, students' performances were evaluated and analyzed with better accuracies. The Artificial Neural Network with its massively parallel network of interconnected analogue processing elements called neurons and with the parallel nature of the neural network we achieved computation accuracies not attainable by conventional statistical methodology.

The objectives of this paper is to (i) determine the cognitive factors that affects students' academic performance. (ii) develop and implement an Artificial Neural Network using Multilayered Feed forward Algorithm to evaluate students' academic performance given the factors so discovered. (iii) evaluate students' performances using their cognitive abilities as a yardstick for evaluation in view of giving each student a fair platform for evaluation. We accomplished this by adopting the following methodology: (i) Reviewed and studied relevant literatures on Artificial Neural Networks, Intelligent Quotient measuring, Factors that affect academic performances, and psychology. (ii) Studied and understood the characteristics of the existing systems, existing parameters and factors used for tracking, testing and predicting students' performances as well as gathered students' data from relevant stakeholders. (iii) explored the system analysis and the design tool required to develop the system. (iv) Employed the Visual Studio and DEV C++ compiler in implementing, training and testing the Neural Network. From these, we obtained results that proves the efficiency of Artificial Neural Networks as an evaluation tool as well as prove that factors like a student's Intelligent Quotient Rating (IQR), Confidence Level (CoL), Time Management ability and Class Attendance are a much optimal evaluating parameters.

2. Literature Review

M. F. Musso et al. (2013) employed a new methodological approach for the field of learning and education. Although this approach had been widely applied in areas such as computational science, engineering and economics, it was yet to be applied to academic evaluation. They used cognitive and non-cognitive measures of students, together with background information to design predictive models of students' performance using Artificial Neural Networks (ANN).These predictions constituted a true predictive classification of academic performance over a period of one year in advance of the actual observed measure of academic performance. Using a total sample of 864 University students (split into three levels of General Academic Performance GAP; low, mid and high measured by grade-point-average) of both genders, ages ranging from 18 to 25 years, they developed three neural network models that used a backpropagation multilayer perceptron composed of nonlinear units. Two of the models reached a precision of 100% identifying the top 33% and lowest 33% groups respectively. The third model reached precisions from 87% to 100% identifying low, mid and high performance levels for the three groups. The result when compared to those of traditional methods such as discriminant analysis demonstrated greater accuracy.

V. O. Oladokun, A. T. Adebanjo & O. E. Charles-Owoba (2008) built a neural network based on the Multilayer Perceptron with two hidden layers and five processing elements per layer. The network predicted accurately 9 out of 11 of candidates (good data) with either 1st Class or 2nd Class upper, 8 out of 15 of candidates (average data) with a 2nd Class lower and 7 out of 8 of candidates (poor data) with either a 3rd Class or Pass thus demonstrating an accuracy of 82% for the Good, 53% for the Average and 88% for the Poor Classification. This indicated an accuracy of about 74% for the artificial neural network and compared to other traditional methods displayed the potential efficacy of the ANN models as a predictive tool.

Raheela Asif, Merceron A., & Pathan M. K. (2015) applied several predicting methods on data sets (of about 347 students broken into two data sets) containing students' pre-admission data and examination scores of first and second academic year courses in predicting the students' performance at the end of the degree. They recorded an accuracy of 83.65% on data set two which had more data entries using Naïve Bayes algorithm while Artificial Neural Network recorded an accuracy of 62.50%. However, since the results of the Naïve Bayes were not easy to interpret it was termed as not actionable.

Usman O. L. & Adenubi A. O. (2013) used Artificial Neural Networks (ANNs) to develop a model for predicting the final grade of a University student before graduating such student employing data consisting thirty (30) randomly selected students in the Department of Computer Science, who have completed four academic sessions in the University. They trained and simulated the Artificial Neural Network models using the nntool of MATLAB (2008a) software. From the test data evaluation obtained, the ANN model correctly predicted the final grade of the students to an accuracy of 92.7%.

2.1 Artificial Neural Network

One of the most amazing and intriguing studies in the world is the study of the human brain and its mind blowing functionalities. The greatest of all human accomplishments has been achieved by this 1.3kg of gray matter! This of course is traceable to the functional capacity and the wonderful configuration of the human brain – the unique factor that makes man the extraordinary computer of all! The obvious superiority of the brain over conventional computing devices in many information processing tasks motivated the developing of computing structures, called Neural Network (NN), which emulate the structure and functionality of the brain (Atiya A. 1991). Thus, it is the biological models resulting from the study of the brain that birthed the concept of Neural Networks (NN). The organization of the brain is considered when constructing Neural Networks configurations and algorithms. Amir Atiya (1991), in his dissertation, *Learning Algorithms for Neural Networks,* defines neural network as a network of massively parallel interconnected analog processing elements, called neurons. He further maintains that this parallel nature enables the neural network to attain, potentially, computational speeds not attainable by conventional or sequential computers. Artificial neural networks are characterized most adequately as computational models having particular properties which include ability to adapt or learn, generalize or organize data. They consist also of a pool of simple processing units which communicate by sending signal (Krose & van der Smagt, 1996).Different methodological approaches have been employed in evaluating the academic performances of students (M. F. Musso et al. 2013). One of the first methods found in many researches along this field is the use of Statistical methods which includes multiple linear regression and discriminant analysis (Bratan & Stromso, 2006, Vandamme, Meskens & Superby, 2007). Another method of note is the use of Structural Equation Modelling (SEM) to test various approach of academic performance (Fenollar et al., 2007; Minano et al., 2008; Ruban & McCoach, 2005). Noted of these traditional methods is that they failed to consistently show the capacity to reach accurate predictions or classification in comparison with artificial intelligence computing methods (Weiss & Kulikowski, 1991; Maucieri, 2003). These lapses found in statistical methods necessitated further research into the third method of predicting academic performance applying the concept of machine learning using Artificial Neural Network.

Many research materials abound on the subject of the Artificial Neural Network (ANN) model which has been touted by various researchers as a more effective tool in performance prediction and forecasting behaviour of irregular data sets. An Artificial Neural Network (ANN), which is motivated by research into the configuration and functionality of the brain (Atiya A., 1991), has gained a lot of interest from researchers within the last decade. According to Sumam Sebastian, (2016) in his work, an Artificial Neural Network, also called Neural Network (NN), is a model of computation motivated from their biological counterparts. It is a computerized

simulation and representation of the Human Neural System. The neural network is a combination of interconnected groups of artificial neurons processing information via a connectionist methodology to computation.
In practical application, neural networks are applied to data sets that defy linear statistical modeling tools as such neural networks can model complex relationships between inputs and outputs as well as find patterns in the given data sets. Basically, since artificial neural networks require vast collections of data, they are best applied where there is a data warehouse.
Neural Networks Models are applied using a number of architectures based on their methods of processing data. The most popular and most used of this architectures is considered below.

2.1.1 Feed-Forward (Multilayer Perceptron) Neural Networks
The Feed-forward (multilayer perceptron) Neural Networks are back-propagation networks that supports the flow of signal in one direction only from the neurons in the input layer through to the neurons in the hidden layer(s) to the neuron(s) in the output layer. These networks do not have feedback mechanisms (loops) as a result, signal only moves forward from the input nodes to the output nodes (Kalejaye B. A, Folorunso O. & Usman O. L., 2015). The Multilayer Perceptron Neural Network is trained using a set of data called the training set consisting of input data and a corresponding output data (called the target). From research we have found that the Multilayer Perceptron Neural Networkover the last decade has been the most used of all Neural Network Architecture (Sumam S., 2016). Notable of the characteristics associated with this architecture includes:

i. having any number of input neurons, hidden layers (ranging from one to many) and output neurons as desired with respect to the numbers of input parameters to be used, processing accuracy and numbers of output parameters required respectively.
ii. The Multilayer Perceptron Neural Networks employing either the Sigmoid, Tangent or any other activation function to model the input to the desired output.
iii. Having weighted connections that links the input layer to the hidden layers and the hidden layers in turn link to the output layer in strictly one direction of flow.

The Feed-forward Neural Network consist of several layers that are interconnected together with the last layer called the output or visible layer. The problem specification often determines the numbers of neurons employers per hidden layer of the network. This is however achieved by a whole lot of trails and errors during the training phase to specify the numbers of layer that provides a more accurate and optimal result. Difficult problems with very irregular data set require a larger number and size of hidden layers. The data processing can extend over multiple (layers of) units, but no feedback connections are present i.e., connections extending from outputs units to inputs units in the same layer or previous layers. This is achieved by some advanced mathematical definitions where; $\boldsymbol{y_i^{(l)}}$ denotes the output of the $\boldsymbol{i^{th}}$ neuron of layer $\boldsymbol{l}$. ($\boldsymbol{y_i^{(0)}}$ denotes the $\boldsymbol{i^{th}}$ input to the network). The function of the network is defined as;

$$\boldsymbol{y_i^{(l)} = f[\sum_{j=1}^{N_{l-1}} w_{ij}^{(i,l-1)} y_j^{(l-1)} + \theta_i^{(l)}]} \qquad \boldsymbol{l = 1, \ldots, L, i = 1, \ldots, N_l}$$

Where $\boldsymbol{w_{ij}^{(i,l-1)}}$ denotes the weight from neuron $\boldsymbol{j}$ of layer $\boldsymbol{l-1}$ to neuron $\boldsymbol{i}$ of layer $\boldsymbol{l}$, $\boldsymbol{\theta_i^{(l)}}$ is the threshold of neuron $\boldsymbol{i}$ of layer $\boldsymbol{l}$. The function $\boldsymbol{f}$ is taken as a unit step or a sign function or as a sigmond-shaped function, example: $\boldsymbol{f(x) = tanh(x)}$ or $\boldsymbol{f(x) = \frac{1}{1+e^{-1}}}$.

2.2 Performance Evaluation Criteria
Evaluation of students' academic performances are based on certain parameters that are necessary yardstick and tool for measuring the effectiveness of students in a number of selected academic programs or specified tasks requiring skills as depends to a great extent on tests much more closely related to the specific task of the interest. These tests could range from examinations based on taught lessons to cognitive abilities of the subjects. Since there is yet to be a universally accepted scientific definition of intelligence or theories to measure intelligence, the purpose of these evaluations is reduced to predicting future performances of the students being tested based on their individual ability to perform as required in an academic program or in a skilled work task (Fischler M. A. & Firschein O. 1987).
Grade Point Average (GPA), being a traditional statistical method (Mariel et al., 2013) has been considered by numerous studies as the best summary of student learning because of its strong prediction of performance (e.g. Kuncel et al., 2004, 2005) for each particular level of education which informs academic administrators if a student is to be promoted to the next level or not. The GPA is also agreed to be an effective tool in measuring

future life productivity of the student in terms of income earned (Roth & Clarke, 1998) as well as job performance (Roth, Be Vier, Switzer & Schippman, 1996).

Whereas the Grade Point Average (GPA) has been touted as the basis for performance evaluation by some studies there are others who believe that this falls short of adequate evaluation citing cognitive and non-cognitive measures as a better alternative (M. F. Musso et al. 2013).

Deductively, scholars and researchers are divided on the evaluation methods that should be adopted over the others but considering that the University examination process could be cheated, influenced or bypassed altogether then administering cognitive tests as it is often used by Scholarship Awarding Bodies and by industries during interviews in Nigeria could be a much better option. Placing students in course areas that lie within their cognitive and overall abilities would be better achieved if these students are evaluated using cognitive factors. Low performing could perform even better than most if they were to be in course areas that allow them to apply their inert strengths instead of having to cram just to pass end of semester examinations.

2.3 Cognition and Performance Evaluation

Performance evaluation falls short of being fair if the cognitive factors of the students are not considered. Considering that people are gifted differently, it would be more optimal an evaluation if students are evaluated and tested in the areas of their cognitive strengths in order to avoid creating an uneven platform where fishes are forced to climb trees and monkeys are forced to dive in water. Some studies have indicated that there exists a strong correlation between the cognitive abilities of students and academic performances (M. F. Musso et al. 2013). It has been observed that the cognitive make up of students has a very strong relationship with their academic achievements (Colom, Escorial, Chin Shih, & Privado, 2007 cited in M. F. Musso et al. Scholars are however divided on the subject of applying cognitive measures to performance evaluation. It is argued that considering students' cognitive abilities can result to a relatively strong performance evaluation (Colom et al., 2007 cited in M. F. Musso et al. 2013).

From experiment and evaluation, which deviated from the usual examination administered in class, of the thirty (30) students tested with questions that placed a demand on their cognitive abilities (ability to think and solve problems, recognized shapes of the same patterns and objects of the same class) within a set time limit, it was discovered that the ten (9) of the students who are regarded as low performing students by CGPA rating outperformed five (5)of the students rated as high performing students. This brings the focus on the criteria with which students are admitted in courses in Nigerian University: criteria that needs to be reviewed and changed.
Importantly though, including non-cognitive factors such as students' class attendance, from which the students' passion or motivation level could be deduce, ensures generally, better academic performance evaluation.

2.3.1 Intelligent Quotient Rating

Intelligent Quotient Rating (IQR), a measure of a person's ability to analyze facts, learn skills, think and apply these facts and skills to solving real world problems proves to be a very vital criterion in evaluating students' academic performances as it exposes the very core ability of the students. This ability or intelligence is obtained from series of aptitude test that cuts across many aspects of the intellectual capacity of each student.

Using this as a factor, each student is evaluated based on his or her ability to think than cram. A student's IQR tests determines a student's ability to apply the relevant facts and skills learnt in several problem areas.

2.4 Passion and Performance Evaluation

It is an accepted concept from experience that passion displayed via commitment and persistence is a vital virtue required for better academic performance. It is often seen from a theoretical point of view that commitment and perseverance are features of well performing students and are often lacking in those that perform poorly. This concept had been conceptualized systematically by Duckworth, Peterson, Matthews & Kelly (2007). They propose that two dimensions characterize passion or tenacity: perseverance of effort (striving harder to accomplish goals despite the hard-ships faced) and commitment or consistency of interests (showing steady interest over time which in our case was deduced from committed class attendance and participation).

3 Research Methodology

3.1 The University Examining System

In Akwa Ibom State University, which in this case is our case study, we used the examining process as the existing system. This system consists of the stakeholders as illustrated in Figure 1.

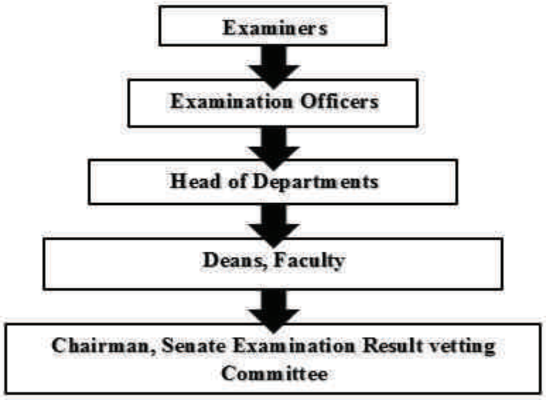


Figure 1: Stakeholders of the University Examination System

The Architecture that is adopted in this system is explained with Figure 2 where students have to sit for examinations set by the examiners. The existing system if properly and carefully implemented is very effective in computing the GPA of students however, there are still some pronounced disadvantages and loops holes in it that could result in embarrassing errors. Some of these disadvantages or problems include:

i. Lacking the capacity to evaluate or predict beforehand the performances of students.
ii. Time and energy wastage associated with the system.
iii. The system being prone to errors since the task of computation is carried out manually which reduces the efficiency of the system.
iv. Longer time taken to correct errors due to the many different hierarchy of validation involved.
v. The system being compromised and subjected to abuse as a result affect its credibility.

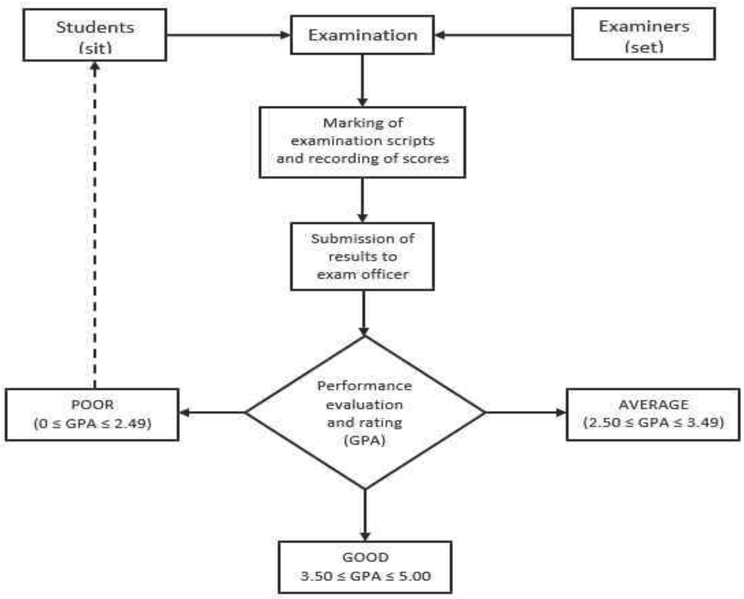


Figure 2: Architecture of the University Examining System

3.2 System Architecture

The conceptual architecture of our model is based on (Kalejaye B. A. et al. 2015) as illustrated in Figure 3. The model consists of the input Data Set (from a text file), the Artificial Neural Network (with the defined activation function with the Multilayer (Back-propagation) Perceptron) and the output text file.

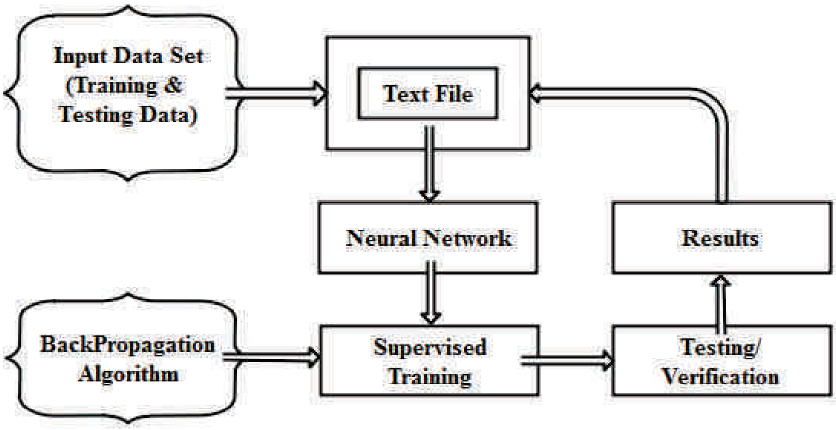


Figure 3: System Conceptual Architecture

Nonlinearity of data is useful for many Artificial Neural Network applications. To achieve a certain level of nonlinearity in the data set, an activation or transfer function is introduced in evaluating the results fed into the neurons of the hidden layer(s) to the output layer. The transfer function defines and outlines the relationship between the inputs and the outputs of the neuron in the network (G. Zhang et al. 2008). Several transfer functions could be applied to a network and according to (G. Zhang et al. 2008), an activation function should be differentiable, bounded and monotonic.

After several experiments with the Sigmoid $f(x) = \frac{1}{1+e^{-1}}$ and hyperbolic tangent (tanh) $f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$functions at separate occasions, the hyperbolic tangent function is adopted in computing the calculation in each neuron. This is largely due to its greater numeric range (from -1 to 1) and the shape of its graph (M. F. Musso et al. 2013). The hyperbolic tangent activation function is use for both the hidden layers and the output layers as agreed by (De Groot and Wurtz 1991; G. Zhang et al, 1998).The hyperbolic tangent function is known to have a higher accuracy curve than the sigmoid function. The derivative of the tangent activation $\frac{d}{dx}\tanh x = 1 - tanh^2$has a memory and time constraint that is very minimal and fast to computes and requires a small memory space using the C++ programming language.The tangent function given as$\tanh x = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$ has an output range of $[-0.1, 1.0]$, which increase the universal range of our network. Using the tangent function requires scaling the output to lie within the range of what the activation function can make thus all target output for the network lie between $-1.0 and 1.0.$

3.3 Implementation of the System

The C++ programing language is employed in this study for the design of the entire Artificial Neural Network. The class diagram in Figure 4 illustrates how the various components of the Network Interact.

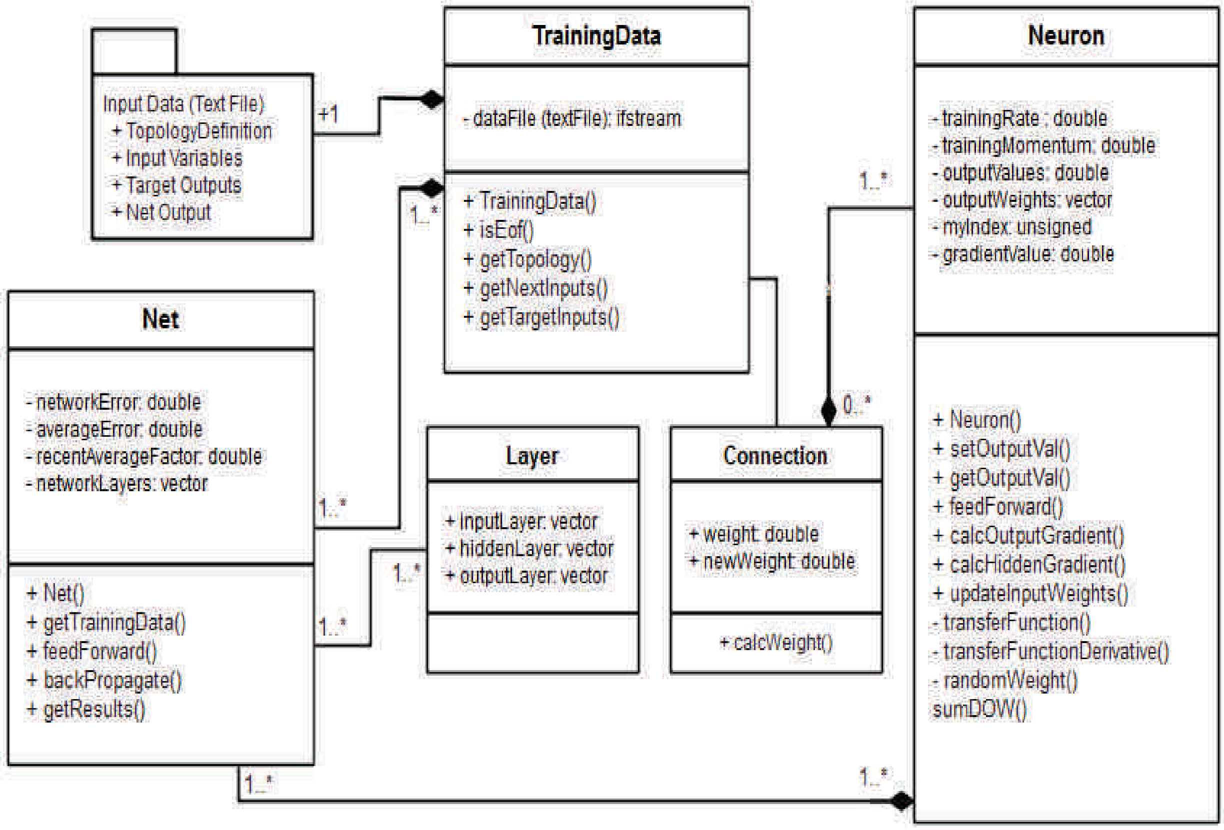


Figure 4: Network Class Diagram.

To train the network, a text file containing the network topology definition with the numbers of neurons in each layer, the training data input and target output was fed into the network and run. the output error of the network is calculated and compared with the input. This enables the evaluation of the accuracy of the network. This work uses the Root Mean Square function for calculating the error. The RMS is defined as;

$\boldsymbol{rms = \sqrt{\frac{1}{n}\sum_i^n(target_i - actual_i)^2}}$. The Artificial Neural Network was trained with an initial training rate of 0.2 and a momentum of 0.5. The final training rate and momentum that gave a more accurate evaluation after several experiments was set at 0.4 and 0.8 respectively.

The challenge associated with building a neural network is vast to say the least. The first of these challenges is collecting the required amount of data enough to train, test and use the network. Another critical design challenge as indicated by many researchers is determining the best architecture to use (V. O. Oladokun et al, 2008), (G. Zhang et al 1998).By architecture, we mean the number of layers, the number of neurons per layer and the number of arcs which links the entire neurons in the network (G. Zhang et al 1998). The issue of which activation function to use for the hidden and output layers also must be considered as well as the training algorithm, normalization methods and test parameters or performance measures.

Determining the number of hidden is rather heuristic, as a result, the most popular way of doing this is mostly by trial and error or by performing repeated experiments (G. Zhang et al, 1998).It has been suggested in many researches that the number of hidden neurons should depend on the number of input patterns with each weight advised to have at least ten input patterns (G. Zhang et al, 1998).Research has found that one single hidden layer is capable of approximating any complex nonlinear function with any desired accuracy (G Zhang et a, 1998, Cybenko, 1989) as a result many works in the field use one hidden layers. It was discovered by Zhang in 1994 that a network with two hidden layers could model underlying data structures and make predictions more accurately that those with one layers. The output layer is the layers that reports the results of the network. Determining the number of neurons on this layer is relatively easy. The number of neurons in the output layer depends on the problem being considered and the output variables desired. For academic performance evaluation, the network could have three output neurons for categorizing students into good, average or poor (V. O. Oladokun et al, 2008).

Taking the above challenges into consideration, we arrived at a network consisting an input layer with having four neurons, two hidden layers with four neurons each and an output layer with a single neuron as shown in Figure 5.

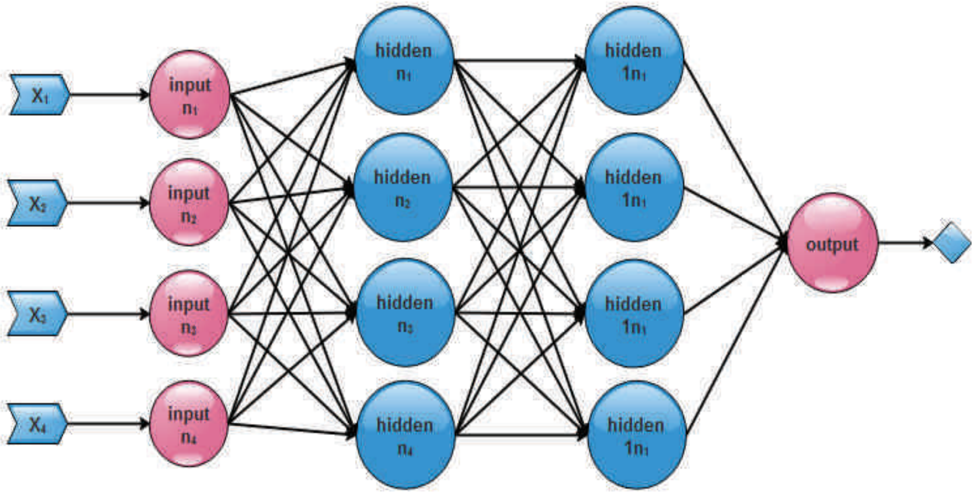


Figure 5: Artificial Neural Network Structural Architecture

3.4 Data Analysis

There exists an interrelationship between several variables that are required in the complex and multi-faceted problem of academic performance evaluation, however, these interrelationships are not often clearly fathomable and comprehended as these interrelationships are mostly nonlinear in nature (M. F. Musso et al, 2013). Research has indicated that ANN have proven to be a very effective approach in addressing situations where characteristics exist. Furthermore, ANN have been used to classify and predict the outcome under these conditions with high level of accuracy but they however require large amount of data sets (M. F. Musso et al. 2013).

In this work, a sample data of two hundred and fifty students were collected from the 200 level, 300 level and final year students in the Department of Computer Science, Akwa Ibom State University and National Open University of Nigeria (NOUN) Nigeria. These sample data include cognitive and non-cognitive variables of the students. ANN researchers are divided on which is a better parameter for predicting academic performance. While some are in favour of using cognitive measures, others believe non-cognitive measures are better. M. F. Musso et al. 2013 however posits that considering both cognitive and non-cognitive variables can strengthen the predictive accuracy of the Neural Network. This work has employed both cognitive and non-cognitive variables. This has increased the nonlinearity of the interrelationships within the data set and the Neural Network has proven its ability to model nonlinear data achieving very high accuracy.

These data set considered variables such as;

i. Students' Time Management Ability
ii. Students' Average Class Attendance
iii. Students' Confidence Level Based on Class Interactions
iv. Students' Intelligent Quotient Score

Scores in some selected first semester courses from 100 final year students studying Computer Science in Akwa Ibom State University and Information Technology from 150 students of the Department of Computer Science, National Open University were collected including the students class attendance for tow academic sessions. The Students' Confidence level obtained are measured by the students' average interactions with lecturers in class by asking intelligent questions and answering questions. The students' Intelligent Quotient Score are measured based on Intelligent Quotient tests answers from printed questionnaire. Using questionnaires, ***time tests*** were administered to the students. The number of questions answered within the stipulated time were recorded for each student, the total number of correct answers within this time were also recorded.

The Students' percentage time management was calculated using the model;

$$\%Time\ Management = \frac{Questions\ answered}{Questions\ given} * 100$$

The Students' Intelligent Quotient Score used the model outlined below;

$$IQ\ Score = \frac{Questions\ answered\ in\ time + Correct\ answers}{Total\ questions\ given} * 100$$

A section of the collected data are shown in the table below.

S/N	% TIME MGT	CLASS ATTENDANCE (32)		CONFIDENCE LEVEL		IQ SCORE
		In Class	% Average	Interactions	% Average	
1	50.45	12	37.5	3	60	90
2	46.43	10	31.25	2	40	81
3	81.67	28	87.5	4	80	125
4	41.02	15	46.875	1	20	100
5	46.56	13	40.625	2	40	116
6	41.32	16	50	3	60	93
7	56	25	78.125	4	80	106
8	67.50	22	68.75	2	40	95
9	73.43	26	81.25	2	40	112
10	78.34	27	84.375	3	60	104
11	70.56	30	93.75	3	60	101
12	57.45	20	62.5	2	40	81
13	86.43	28	87.5	3	60	116
14	62.34	31	96.875	2	40	105
15	78.56	22	68.75	2	40	120
16	67.54	26	81.25	3	60	95
17	78.56	30	93.75	3	60	110
18	71.71	25	78.125	4	80	93
19	74.5	31	96.875	2	40	65
20	81.64	23	71.875	4	80	127
21	45.62	24	75	1	20	105
22	63.44	25	78.125	2	40	105
23	83.34	21	65.625	4	80	100
24	77.56	22	68.75	3	60	113
25	70.84	30	93.75	3	60	96
26	67.6	31	96.875	2	40	99
27	73.7	21	65.625	2	40	78
28	41.6	13	40.625	1	20	124
29	64.5	15	46.875	3	60	105
30	45.4	16	50	1	20	101

Table 1: Sample of Students' Data

The students' Intelligent Quotient Score had the highest momentum and had the highest impact on the Artificial Neural Network (ANN) as shown in the graph below.

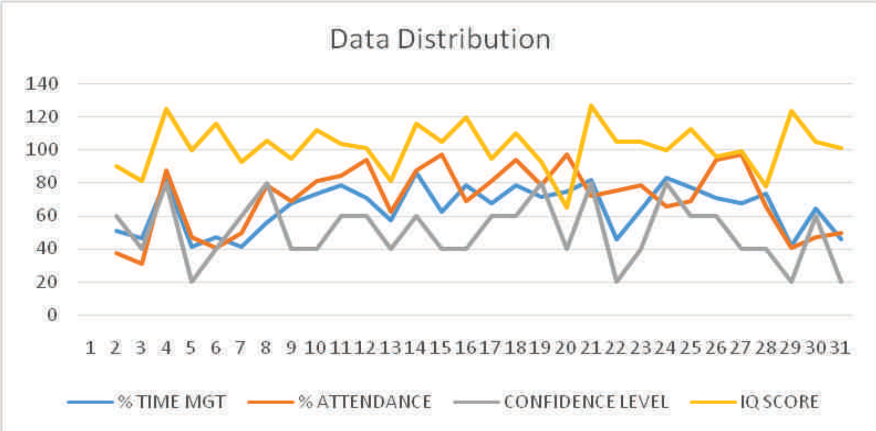


Figure 6: Graph for Data Distribution

The weight variations as updated by the ArtificialNeural Network given the data above with the initial weights and updated weights after five passes is shown below.

Table 2: Weight Variations and Update by the Network

Initial Weights	Pass 1	Pass 2	Pass 3	Pass 4	Pass 5
0	-0.00034	-0.00051	-0.00026	-0.00013	-6.38E-05
0	-0.00034	-0.00051	-0.00026	-0.00013	-6.36E-05
0	-0.0003	-0.00046	-0.00023	-0.00011	-5.68E-05
0	-0.00034	-0.0005	-0.00025	-0.00013	-6.26E-05
0	-0.00034	-0.00052	-0.00026	-0.00013	-6.43E-05
0	-4.15E-06	-6.24E-06	-3.12E-06	-1.55E-06	-7.74E-07
0	-4.15E-06	-6.24E-06	-3.12E-06	-1.55E-06	-7.74E-07
0	-4.15E-06	-6.24E-06	-3.12E-06	-1.55E-06	-7.74E-07
0	-4.15E-06	-6.24E-06	-3.12E-06	-1.55E-06	-7.74E-07
0	-4.15E-06	-6.24E-06	-3.12E-06	-1.55E-06	-7.74E-07
0	-5.63E-06	-8.46E-06	-4.23E-06	-2.11E-06	-1.05E-06
0	-5.63E-06	-8.46E-06	-4.23E-06	-2.11E-06	-1.05E-06
0	-5.63E-06	-8.46E-06	-4.23E-06	-2.11E-06	-1.05E-06
0	-5.63E-06	-8.46E-06	-4.23E-06	-2.11E-06	-1.05E-06
0	-5.63E-06	-8.46E-06	-4.23E-06	-2.11E-06	-1.05E-06
0	-7.20E-05	-0.00011	-5.41E-05	-2.70E-05	-1.34E-05
0	-7.20E-05	-0.00011	-5.41E-05	-2.70E-05	-1.34E-05
0	-7.20E-05	-0.00011	-5.41E-05	-2.70E-05	-1.34E-05
0	-7.20E-05	-0.00011	-5.41E-05	-2.70E-05	-1.34E-05
0	-7.20E-05	-0.00011	-5.41E-05	-2.70E-05	-1.34E-05
0	-1.69E-05	-2.54E-05	-1.27E-05	-6.34E-06	-3.15E-06
0	-1.69E-05	-2.54E-05	-1.27E-05	-6.34E-06	-3.15E-06
0	-1.69E-05	-2.54E-05	-1.27E-05	-6.34E-06	-3.15E-06
0	-1.69E-05	-2.54E-05	-1.27E-05	-6.34E-06	-3.15E-06
0	-1.69E-05	-2.54E-05	-1.27E-05	-6.34E-06	-3.15E-06

The weight variations is graphically illustrated below.

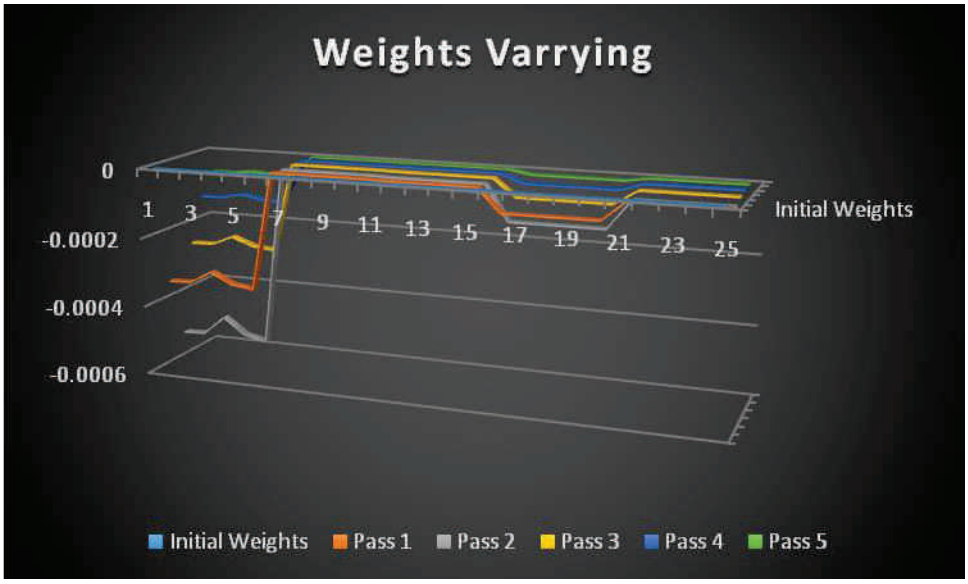


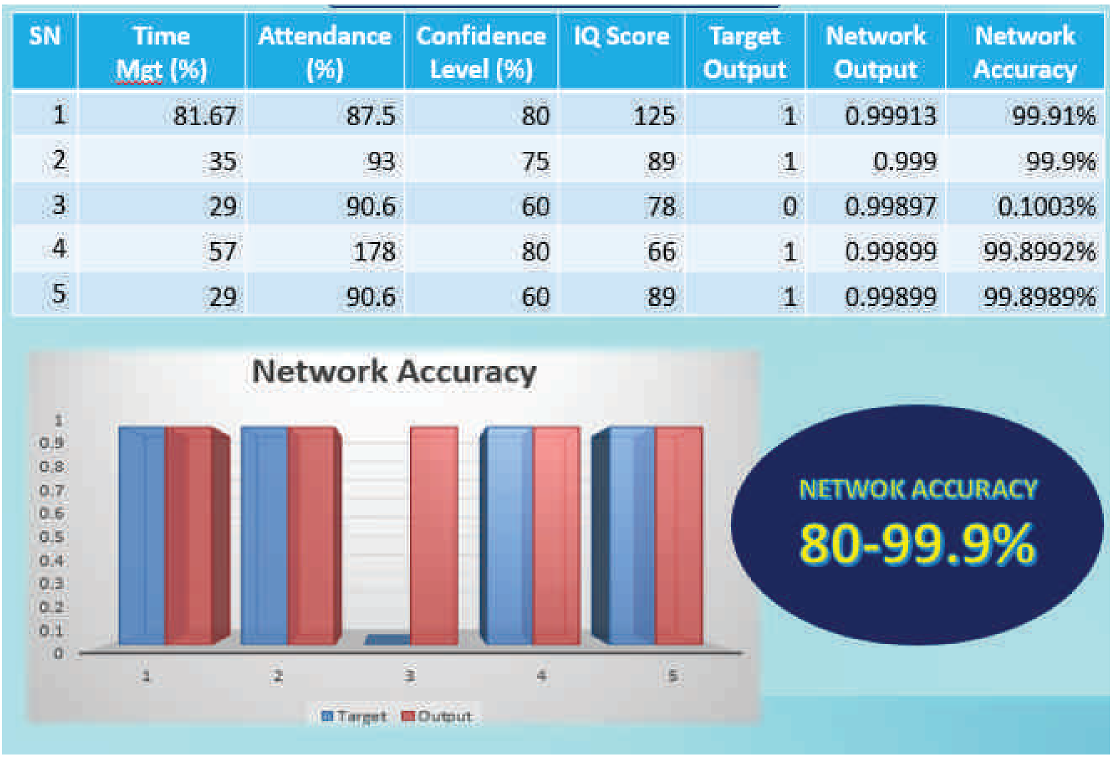
Figure 7: Graph for Weight Variations

4 Results and Discussions

This paper presents a discussion into the concept of implementing an Artificial Neural Network using the C++ Programming Language and applying same for student's academic performance evaluation using cognitive factors of time management, confidence level and IQ scores as well as non-cognitive variable of class attendance. In the study, the Final Year Students of the Department of Computer Science, Akwa Ibom State University were observed for two sessions from their 300 through 400 level. During this period, the class attendance, class participation for each students was recorded. Increased class attendance and interactions were recorded in courses that students have a liking for. It was deduced that poor performances are associated with students placed in Departments outside their cognitive strengths.

Using a printed questionnaire covering general IQ questionscovering specified areas of reasoning, the IQ Scores of the students and their time management abilities were obtained. Using these data set collected from the students as outlined in Table 1, the Artificial Neural Network was trained until the system output was close to the target output a with an accuracy of 94.3%. The updated weights at this point were saved and used as used as the weights for our trained system. The input parameters of any student to be tested is entered into a text file and fed into the system and based on these parameters, the network supervisor sets a target output within the range of the tangent function $[-1.0, 1.0]$.

Testing the Artificial Neural Network given the inputs for five students with expected outputs (targets) the Neural Network gave the following results as summarized in Figure 6 below.



SN	Time Met (%)	Attendance (%)	Confidence Level (%)	IQ Score	Target Output	Network Output	Network Accuracy
1	81.67	87.5	80	125	1	0.99913	99.91%
2	35	93	75	89	1	0.999	99.9%
3	29	90.6	60	78	0	0.99897	0.1003%
4	57	178	80	66	1	0.99899	99.8992%
5	29	90.6	60	89	1	0.99899	99.8989%

Figure 8: Neural Network Accuracy

5. Conclusion

Evaluation of students' academic performances is a now becoming a challenging issue given the rate at which the manual system is being cheated by many of its stake holders as a result a system for evaluating academic performance of students, especially based on the cognitive abilities of each student, such as this is a necessary. This work has been able to analyze an Artificial Neural Network and its functionalities as well as discuss some of the factors that should be considered in evaluating a student performance. This work has opened a very big window of understanding for me in the area of Artificial Neural Network and its applications.

This research work has achieved success in implementing an Artificial Neural Network that evaluates students' academic performances using the student's cognitive ability of IQ Scores (IQ rating) as one of the variables and yardstick for evaluating performance. Also some determined factors that could affect the academic performances of students in the Department of Computer Science with special focus on their cognitive strengths have been discussed in this work.

This work has shown the efficiency and effectiveness of an Artificial Neural Network in academic performance evaluation. Based on the four input variables inputted into the system, the model achieved an accuracy of 99.9% which illustrates how efficient an Artificial Neural Network is at evaluation and predicting as a result it becomes a tool much needed tool in academic management.
From this work, we see that a student Intelligent Quotient (Common Sense) when combined with their attention in class as well as class attendance is a factor that influences the performances of students. The mental capacity of a student can be improved by conscious mental exercises such as engaging in creative and logical thinking, mental calculations as well as taking on challenging IQ test questions.

5.1 Contributions/Areas of Applications

Academic performance evaluation is much relevant in the academics. The very success of an academic institution is based on the overall performances of her students. This work has strengthened the claim that both cognitive and non-cognitive parameters are necessary for a more balanced evaluation of results. This work has shown that Intelligent Quotient of students should be considered as a testing parameter. Academic performance evaluation of students using ANN can be applied and used as follows:

i. **University Admission Management:** With the scrapping off of the University Matriculation Examination by the National Universities Commission (NUC), this system can be employed by Universities as a pre-admission evaluation tool thus ensuring students are placed in study areas where they are more likely to do best. To achieve this, the input parameter for the network could be varied across a variety of cognitive inputs as required.

ii. **Change of Department Evaluation Tool:** Using this system, academic managers can place students who could not do well in a study area or Department to another area or Department where the students have been evaluated to have a better chance of performing their best. The accepting Department could use this system to evaluate the students' performance using cognitive abilities unique to each student. This will reduce the cases of withdrawal from study.

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